

RPNG

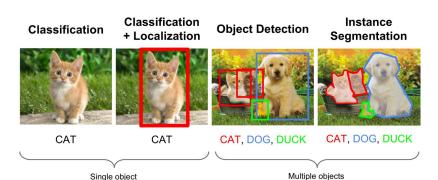
Background on Deep Learning

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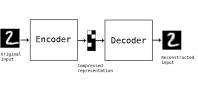
Popular Deep Learning Tasks

- Classification
- Classification + Bounding Box Detection
- Muti-object detection
- Pixel-wise semantic segmentation

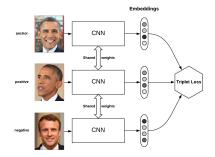


More Popular Deep Learning Tasks

- Embeddings (dimension reduction)
 - Autoencoder
 - Triplet Embedding



Autoencoder



Triplet embedding

Fully Connected Layer

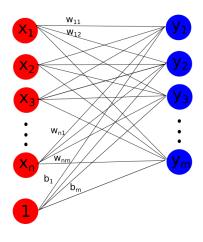
- Vector input and output
- Learned weights associated with each connection
- Can be written as a linear operation

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \dots & x_n & 1 \end{bmatrix}^{\mathsf{T}}$$

$$\mathbf{y} = \begin{bmatrix} y_1 & y_2 & \dots & y_m \end{bmatrix}^{\mathsf{T}}$$

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} & b_1 \\ w_{21} & w_{22} & \dots & w_{2n} & b_2 \\ \vdots & \ddots & \ddots & \vdots & \vdots \\ w_{m1} & w_{m2} & \dots & w_{mn} & b_m \end{bmatrix}$$

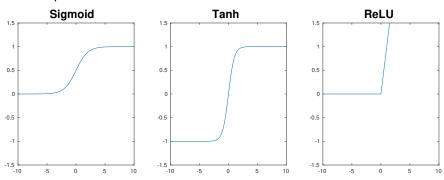
$$y = Wx$$



Nonlinear Activation

- Fully connected layer cannot model nonlinear functions
- Nonlinear activations are used to provide nonlinearity
- Key idea: they resemble a "neuron" firing

Examples:



Popular activation functions

Convolution Layer

- Matrix/Tensor input and output
- Useful for image input

X ₁₁	X ₁₂	X ₁₃	X_{14}	X ₁₅	X_{16}	X ₁₇
X ₂₁	X ₂₂	X ₂₃	X ₂₄	X ₂₅	X ₂₆	X ₂₇
X ₃₁	X ₃₂	X ₃₃	X ₃₄	X ₃₅	X ₃₆	X ₃₇
X ₄₁	X ₄₂	X ₄₃	X ₄₄	X ₄₅	X ₄₆	X ₄₇
X ₅₁	X ₅₂	X ₅₃	X ₅₄	X ₅₅	X ₅₆	X ₅₇
X ₆₁	X ₆₂	X ₆₃	X ₆₄	X ₆₅	X ₆₆	X ₆₇
X ₇₁	X ₇₂	X ₇₃	X ₇₄	X ₇₅	X ₇₆	X ₇₇

$$Y_{ij} = K_{33}X_{i,j} + K_{32}X_{i,j+1} + K_{31}X_{i,j+2} + K_{23}X_{i+1,j}$$

$$+ K_{22}X_{i+1,j+1} + K_{21}X_{i+1,j+2} + K_{13}X_{i+2,j}$$

$$+ K_{12}X_{i+2,j+1} + K_{11}X_{i+2,j+2} + b$$

Max Pooling Layer

- Useful for viewpoint invariance
- Similar operation to convolution

Single depth slice

x 1 1 2 4 5 6 7 8 3 2 1 0 1 2 3 4

max pool with 2x2 filters and stride 2



Softmax Layer

- Bounds output to [0,1]
- Sum of output is 1
- Useful for learning probability mass functions

Suppose $\mathbf{x} \in \mathbb{R}^n$, then

$$Softmax(x_i) = \frac{e^{x_i}}{\sum_{i=1}^n e^{x_i}}$$

Loss Function

- A scalar error metric for the network
- Necessary for training. Otherwise there is no optimization criteria

Popular examples:

Cross Entropy

Suppose $\mathbf{x} \in \{0,1\}^n$ is the ground truth class labels and $\hat{\mathbf{x}} \in [0,1]^n$ is the output of a classification network, then

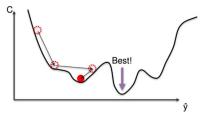
$$E(\mathbf{x}, \hat{\mathbf{x}}) = -\sum_{i=1}^{n} x_i \ln(\hat{x}_i)$$

MSE Suppose $\mathbf{x} \in \mathbb{R}^n$ is the ground truth and $\hat{\mathbf{x}} \in \mathbb{R}^n$ is the output of a *regression* network, then

$$E(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{n} ||\hat{\mathbf{x}} - \mathbf{x}||_2^2$$

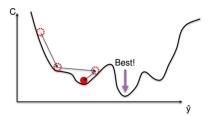
Optimization

- Suppose we have a feed-forward neural network with arbitrary tensor input X, output (loss/error) E, and layers L₁, L₂,..., L_k (including loss layer).
- How can we optimize such a complicated function?
- There are many local minimums to get caught in



Optimization

- Suppose we have a feed-forward neural network with arbitrary tensor input X, output (loss/error) E, and layers L₁, L₂,..., L_k (including loss layer).
- How can we optimize such a complicated function?
- There are many local minimums to get caught in
 - Idea: Look at each layer separately
 - Observe that $E = L_k(L_{k-1}(...(L_1(X))))$.
 - We can estimate the gradient of the entire network with the chain rule!



Optimization: Stochastic Gradient Descent

- Create copies of your network
 - Train on multiple data samples at once (i.e., a batch)
 - Average out the loss values across examples
 - Make sure the examples are selected randomly
- At each iteration, estimate the gradient of each layer w.r.t. the weights
- Update the weights with the average gradient over the batch with a scalar multiplier called the *learning rate* (typically << 1)

Suppose we have the weights of layer L_i , at iteration j, $\boldsymbol{W}_i^{(j)}$, with layer input \boldsymbol{X} , learning rate η , and n examples per batch. Then the update step is:

$$\boldsymbol{W}_{i}^{(j+1)} = \boldsymbol{W}_{i}^{(j)} - \frac{\eta}{n} \sum_{k=1}^{n} \frac{\partial L_{i}(\boldsymbol{W}_{i}^{(j)}, \boldsymbol{X}_{k})}{\partial \boldsymbol{W}_{i}^{(j)}}$$

Implementation

Popular Libraries:

- TensorFlow
- Keras
- Caffe (Caffe2 as well)
- PyTorch
- MXNet
- Darknet



The slides and code for the tutorial can be found at:

https://github.com/nmerrill67/DeepLearningTutorial

We will step through the script together.